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Organic farming and greenhouse gas emissions: A longitudinal U.S. state-level study

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ABSTRACT

Organic farming practices, focused on agro-ecological health, have long been centered on the idea that such approaches reduce resource intensity, improve soil health, reduce environmental burdens, and improve crop quality. These approaches can also mitigate climate change impacts. Our research examines the relationship between organic farming and greenhouse gas (GHG) emissions. Using U.S. state-level data over the 1997–2010 period, we estimate that a one percent increase in organic farming acreage could reduce GHG emissions by 0.049%. We also find that the impact of organic farming on methane and nitrous oxide emissions varies with the share of transportation output. Put in context, at the current shares of transportation output, organic farming is expected to mitigate methane and nitrous oxide emissions across most states. The connection between transportation and organic farming suggests that the environmental harm of transportation output embodied in organic food production might be too negligible to outweigh the environmental benefits of organic farming. The current study provides evidence supporting potential GHG mitigation benefits associated with organic food production. Policymakers and scientists can build on these results to further develop the evidence base and policies needed to quantify and maximize the benefits of adopting organic farming practices.

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1. Introduction

Pre-industrial agricultural practices typically relied on few off-farm inputs and utilized traditional approaches to plant, fertilize, and irrigate cropland to maximize crop yields. While many of these practices are consistent with the modern notion of organic farming, Lord Northbourne is credited for having been the first person to use the term "organic" to describe the alternative farming process currently practiced worldwide (Paull, 2014). Northbourne (2003) warned that the reliance on synthetic fertilizers and pesticides deprived farms of "biological completeness" (p. 96). Northbourne's holistic view was that a farm had to be treated as a living organism where the soil, microorganisms, insects, and plants were naturally symbiotic. He encouraged the use of biodynamic practices in organic farming based on the work of Steiner (2004), which involved a focus on revitalizing soil health and fertility.

Organic farming practices, focused on agro-ecological health, have long been centered on the idea that such approaches reduce resource intensity, improve soil health, reduce environmental burdens, and improve crop quality (Kuepper, 2010). Current thinking has further evolved to posit that the adoption of organic farming practices worldwide can be a significant and sustainable means to tackle climate change. Indeed, such practices have the potential to sequester up to one third of current anthropogenic emissions (Jordan et al., 2009). Organic agriculture owes this ability to its reliance on natural ecological processes in land, soil, and crop management in lieu of synthetic inputs. As a result, soils that are managed using organic practices are likely to be not only healthier but also more resilient to extreme weather events (Niggli et al., 2009).

Organic farming practices can mitigate GHG emissions in a number of ways. First, limiting the application of synthetic fertilizers, herbicides, pesticides, and fungicides and their high embodied energy can potentially reduce GHG emissions and the runoff of nitrate and toxic chemicals. It is estimated that the total energy needs covering all stages of the lifecycles of nitrogen, phosphorous, and potash exceed 90 GJ per metric ton (Bhat et al., 1994). On the other hand, the total energy needs for the

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Acronyms and abbreviations

EKC	Environmental Kuznets Curve
EPA	Environmental Protection Agency
GDP	Gross domestic product
GHG	Greenhouse gas
IFOAM	International Federation of Organic Agriculture Movement
IPAT	Mathematical identity for environmental impact as a function of population, affluence, and technology
LCA	Lifecycle analysis
LUCF	Land-use change and forestry
MTCE	Metric tons of CO_2e
NOP	National Organic Program
SIT	State Inventory Tool
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
USDA	United States Department of Agriculture
VMT	Vehicle Miles Traveled
WRI	World Resources Institute

production of the active ingredients used for major U.S. herbicides, pesticides, and fungicides are estimated to exceed 816 GJ per metric ton (Bhat et al., 1994). Second, the use of cover crops, crop rotations, and compost in organic farming can play an important role in maintaining optimal soil health, increasing carbon sequestration, and reducing GHG emissions. Cover crops can limit competition for nutrients with weeds and reduce water runoff and evaporation. They also represent a nitrogen sink especially for subsequent crops (Hartwig and Ammon, 2002). As for crop rotation, it can increase groundwater storage (Dakhlalla et al., 2016), enhance microbial richness and diversity (Venter et al., 2016), and lower N_2O emissions (Petersen et al., 2006). Finally, organic farming can eliminate emissions from waste by converting organic waste into compost for use as fertilizer.

With the agricultural sector accounting for about 24% of global carbon emissions (IPCC, 2015), it represents a promising carbon mitigator and a potentially significant net carbon sink. In fact, the annual mitigation potential for agriculture has been estimated at 6 Gt of CO_2e, with soil carbon sequestration contributing about 89% to this potential (Bellarby et al., 2008). In addition, the economic value of ecosystem services in organic farming can range from $1610 to $19,420 per hectare (ha) per year versus $1270 to $14,570 in conventional farming, whereas non-market ecosystem services in organic farming can range from $460 to $5240 per ha per year versus $50 to $1240 in conventional farming (Sandhu et al., 2008).

Despite increasing consumer interest in organic foods, there has been some inconsistency in conclusions of studies on the environmental impact of organic farming, with some reporting a positive association (e.g. Wood et al., 2006), a negative association (e.g. Cooper et al., 2011) or no statistically significant difference across organic and conventional sites (e.g. Syväsalo et al., 2006). Admittedly, there are concerns that the increase in land use arising from a larger organic farming sector could increase carbon emissions and reduce global carbon sequestration capacity. Combined with the concerns about climate change and the environmental implications of food production, there is an urgent need to more thoroughly understand organic food production's association with GHG emissions, alongside conventional practices.

Most previous research addressing this relationship has been based on site-specific methods contrasting emissions across organic and conventional sites. For instance, lifecycle analysis (LCA) is a common tool used to assess the environmental impact of farming. LCA uses a "ground-up" approach, which considers the impacts of individual stages of a product's lifecycle and can involve the use of different data sources and underlying assumptions about energy consumption across studies, especially those analyzing the same products (Ayres, 1995). LCA research often lacks generalizability and yields estimates that vary depending on products, product groups, geography, methodology, and data. This does not imply that LCA is inappropriate for addressing this paper's theme. In fact, it can provide compelling insight when combined with other management tools and when applied within a consequential or dynamic framework (e.g. Dyckhoff and Kasah, 2014; Vázquez-Rowe et al., 2013).

Rather than focus on specific sites, this paper examines the relationship between organic food production and greenhouse gas emissions at the U.S. state level. This approach yields estimates measuring the proportionate change in greenhouse gas emissions arising from a change in organic food production. These estimates measure the net state-level environmental impact of organic food production, and in this respect allay concerns about lack of generalizability arising from idiosyncratic differences across sites. In addition, by using appropriate data and empirical models, we expect to produce reliable results and policy implications of potential interest to environmentalists, policymakers, and activists. To this end, this paper is organized as follows: Section 2 provides background information about organic farming in the United States. Section 3 summarizes the relevant literature. Section 4 describes the data and empirical strategy. Section 5 summarizes the estimations results. Section 6 discusses the results and concludes.

2. Background

Organic farming is a crop and livestock production system that forgoes off-farm inputs for maintaining healthy interactions between soil biological activity, cycles, and biodiversity. The Organic Foods Production Act of 1990 introduced the United States Department of Agriculture's (USDA) National Organic Program (NOP) to provide systematic oversight of organic certification of food production in the United States (Kuepper, 2010). The NOP is designed to prevent producers from claiming that their food is organic unless they have satisfied certain standards. Broadly speaking, producers are not permitted to use any substances prohibited by the NOP in their land for at least three years before their first organic harvest. They are also required to manage soil health through tillage, crop rotations, cover crops, composting, and animal waste. Furthermore, pest control and weed management are primarily handled using biological and manual practices and in exceptional cases using approved synthetic substances (Kuepper, 2010).

The organic farming sector in the United States grew from 1.77 million acres in 2000 to 5.3 million acres in 2011 (USDA, 2013) and from $3.6 billion in sales in 1997 to $43.3 billion in 2015 (OTA, 2016). In 2014, average organic cropland in the United States represented less than 1% of total state farmland despite organic food sales making up about 5% of total food sales (OTA, 2016). Fig. 1 shows that average state-level organic cropland barely represented 0.54% of total state farmland in 2010, up from about 0.19% in 2000. On the other hand, organic sales did not exceed 9% of total farming sales in Vermont in 2007 and were below 3.5% across the rest of the states, with the vast majority falling below 1% (USDA, 2013).

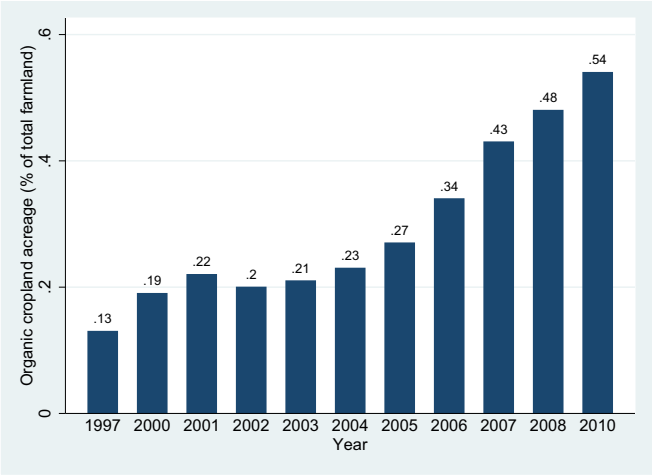

Fig. 1. Average state-level organic cropland acreage (% of total farmland) (Data Source: USDA).

3. Summary of previous research

Previous assessments of the environmental impact of organic food production have yielded mixed results largely due to high variability in LCA research across products, product groups, and geography. The following represent examples of relevant previous research, which are also summarized in Table 1.

In a study using a randomized complete block design, the sustainability of apple production was examined across organic, conventional, and integrated (i.e. combination of organic and conventional) systems in Washington state (Reganold et al., 2001). The organic system was found to be more sustainable across a number of areas. First, there was no statistically significant difference in yields across the three sites. Second, the organic system was found to have better soil quality and a lower environmental footprint. Third, organic apples were found to be tastier than those from other systems. Finally, the organic system was found to be more profitable and energy efficient. The study highlighted the importance of accounting for ecosystem processes in the provision of economic incentives to growers.

Another study using LCA based on an input-output framework estimated differences in environmental impact across organic and conventional farming sites in Australia (Wood et al., 2006). The study found that direct energy use, energy related emissions, and greenhouse gas emissions were higher in the organic site, but argued that accounting for indirect contributions, emissions could be higher in the conventional site.

Following an approach similar to that applied by Reganold et al. (2001), three farming systems were compared in Western Finland (Syväsalo et al., 2006). GHG fluxes and nitrogen leaching and concentration were compared in grass production and livestock raising across organic and conventional production systems and were measured in cereal production without livestock under conventional production. There was no statistically significant difference in measured GHG emissions between organic and conventional plots. In contrast, however, Cooper et al. (2011) used LCA but found emissions to be much larger per hectare in conventional farms.

In a meta-analysis of 71 studies covering 170 cases, the environmental impact of organic farming was assessed relative to conventional farming (Tuomisto et al., 2012b). The study found soil organic matter to be 7% higher in organic farms and estimated nitrogen leaching in organic farms to be 31% lower per unit of area but 49% higher per unit of product. The analysis associated the lower nitrogen level to fewer nitrogen input applications and the higher nitrogen level to a mismatch between nitrogen availability and a crop's nitrogen intake. It also posited that lower nitrogen leaching per unit of product arose from the use of cover crops in organic farming. The study also found that organic farms used 21% less energy.

In 2009, the International Federation of Organic Agriculture Movement (IFOAM) compiled case studies contrasting organic farming with its conventional counterpart across a number of countries, of which the most notable were the United States, the Netherlands, Egypt, and Switzerland. The American case was based on Rodale Institute's farming trials, which assessed energy use, carbon sequestration, and yields in the production of corn, wheat, and soybeans. The conventionally managed system was estimated to use 30% more energy than its organic counterpart (IFOAM, 2009).

Table 1
Summary of relevant previous research.

Contribution	Methodology	Scope	Main finding
Reganold et al. (2001)	LCA	USA	Organic apple site produced similar yield as other sites. Organic site had better soil quality and lower environmental impact. Organic site also produced tastier apples and was more profitable & energy efficient.
Mäder et al. (2002)	LCA	Switzerland	Organic site requires less nutrient and energy input.
Pimentel et al. (2005)	LCA	USA	Soybean and corn yields are similar across all systems under normal rainfall and higher in the organic systems under drought conditions. Organic systems use less fossil energy inputs and have higher soil carbon and water content.
Wood et al. (2006)	LCA	Australia	Organic site uses more energy and emits more GHG emissions. Accounting for indirect contributions could reverse the finding.
Syväsalo et al. (2006)	LCA	Western Finland	No statistically significant difference across organic & conventional sites.
Bos et al. (2007)	LCA	Netherlands	Organic dairy farms emit fewer emissions than conventional farms.
IFOAM (2009)	LCA	USA	Conventional site uses more energy than organic site.
Luske and van der Kamp (2009)	LCA	Egypt	Composting increases soil carbon in reclaimed desert soils
Cooper et al. (2011)	LCA	UK	GHG emissions per hectare are higher in conventional farms
Tuomisto et al. (2012b)	Meta-analysis	71 studies	Soil organic matter is higher in organic sites. Nitrogen leaching is lower in organic sites per unit of area but higher per unit of product.
Lee et al. (2015)	Meta-analysis	107 studies	Effect of organic farming varies depending on data source, sample size, farm products, cropping patterns, and measurement unit.
McGee (2015)	Regression	USA	Organic farming is associated with increased GHG emissions.
Ghimire et al. (2017)	LCA	USA	Organic and reduced-tillage systems sequester more carbon than conventional system and have negative global warming potential.
Lori et al. (2017)	Meta-analysis	56 studies	Organic systems have more enhanced soil microbial activity.

The annual carbon sequestration potential for the organic system was estimated to reach 2.3 metric tons per hectare and organic yields were found to be 28–34% higher especially during dry and wet seasons.

These farming trials were also utilized in Kutztown, Pennsylvania to contrast conventional, organic animal-based, and legume-based organic systems (Pimentel et al., 2005). Soybean and corn yields were found to be similar across all systems under normal rainfall and higher in the organic systems under drought conditions. Organic systems were also found to use less fossil energy inputs and to have higher soil carbon and water content.

A similar farming trial spanning over 21 years was conducted in Switzerland. The trial was referred to as the DOK (bio-Dynamic, bio-Organic, and Konventionell) system comparison trial, which compared soil fertility, nutrient input, energy input, and yields across organic and conventional farming systems. These systems were for the production of grass-clover, potatoes, and winter wheat. The results of the DOK trial were covered by a number of studies (Mäder et al., 2002; Fließbach et al., 2007; Leifeld et al., 2009). In particular (Mäder et al., 2002), estimated that the organic system required 34%–51% less nutrient input and 20%–56% less energy input than the conventional system. Yields, on the other hand, were found to be lower in the organic system across all analyzed crops.

The Dutch case was based on a meta-analysis contrasting GHG emissions in organic and conventional dairy farms across the Netherlands (Bos et al., 2007). It estimated organic dairy farms to emit between 11 and 17 metric tons of CO_2e (MTCE) per hectare and between 1.31 and 1.46 MTCE per 1000 kg of milk versus between 14.5 and 34 MTCE per hectare and between 1.45 and 1.65 MTCE per 1000 kg of milk in their conventional counterparts. The lower emissions in the organic dairy farms were attributed to the absence of chemical fertilizers, less reliance on concentrate feed, and increased grazing.

The Egyptian case focused on the effectiveness of composting in improving the carbon content of reclaimed desert soils (Luske and van der Kamp, 2009). The compost applied to the trial farms consisted of chicken and cow manure, rice straw, and green waste procured locally. Over a 30-year period, the per-hectare soil carbon stock increased from 3.9 metric tons to 30.3 metric tons, resulting in an annual increase of 0.85 metric tons per hectare.

In one of the most comprehensive studies to date, a meta-analysis of 107 studies published between 1977 and 2012 assessed the environmental impact of organic farming (Lee et al., 2015). The study found that the effect of organic farming on energy intensity varied depending on data source, sample size, and farm products, whereas the effect on greenhouse gas emissions varied depending on farm products, cropping patterns (i.e. monocropping versus multicropping), and measurement unit (i.e. emissions per area versus per unit).

Recent studies have provided evidence supporting organic farming as a sustainable choice. For instance, in an examination of GHG emissions, soil organic matter, and global warming potential across conventional (CT), reduced-tillage (RT), and organic systems (OR), RT and OR systems had higher soil organic carbon sequestration and a negative global warming potential (vs. positive global warming potential for the CT system) (Ghimire et al., 2017). This is further supported by a meta-analysis of 56 studies published between June 2015 and February 2016, which analyzed soil health across different farming systems (Lori et al., 2017). This study found organic systems to have 32–84% more soil microbial activity as captured by microbial biomass carbon and nitrogen, fatty-acids, and other activities.

Of particular relevance to this paper, McGee (2015) examined the relationship between organic farming acreage and agricultural emissions using multiple regression analysis. The study found that organic farming at the U.S. state level was associated with more GHG emissions. It made use of data from the World Resources Institute, which disaggregates state emissions into specific sectors and data from the USDA on total farmland and organic cropland acreage. However, the fact that environmental emissions data and acreage are at least in part from the same source raises important concerns. More specifically, the data used for the response variable (emissions) are by construction similar to those for the key predictor variables (total farmland and organic cropland acreage). In particular, emissions from the agricultural sector are constructed using data from the USDA, Commercial Fertilizers report, and the Fertilizer Institute (WRI, 2015). This is especially problematic for total farmland acreage, which is likely highly correlated with agricultural emissions. Increased farmland acreage will inevitably result in an increase in the use of pesticides, fertilizers, herbicides, and fungicides, which in turn will increase GHG emissions. Based on the same data that McGee used for his analysis, correlation between these total farmland and agricultural emissions is estimated at 0.75 versus 0.55 when using total GHG emissions. On the other hand, correlation between agricultural emissions and organic cropland acreage is estimated at 0.47 versus 0.21 when using total GHG emissions. Thus, positive association between organic farming acreage and emissions is not surprising when both variables are highly collinear.

Another surprising dimension in McGee's analysis is the contention that organic farming practices harm the environment is connected to what he dubbed as the “displacement paradox theory.” The rationale is that an expansion of organic farming practices may not necessarily result in the displacement of conventional farming practices. Rather, market forces can create the necessary conditions for the addition of organic food products to existing markets. In other words, consumers of organic products would represent new demand, with no noticeable impact on the demand for conventionally produced products. McGee (2015) also added that higher emissions were likely caused by lax USDA organic production standards and the corporatization and scaling of organic farming operations especially to compensate for lower yields under organic production.

In sum, LCA studies provide a large range of estimates that are not readily generalizable. As a result, the over-reliance on LCA blurs our understanding of the environmental impact of organic farming. Nevertheless, despite such ambiguity, the organic farming system appears to generally be more sustainable than its conventional counterpart. In the next sections, we depart from LCA research by using U.S. state-level data to examine the net environmental impact of organic farming.

4. Data and empirical strategy

4.1. Data

We make use of U.S. state-level data over the 1997–2010 period, excluding years 1998, 1999, and 2009, which are missing from USDA data. Organic acreage data are also available from the USDA only from 1997. As a result, other datasets are restricted to the 1997–2010 period. All 50 U.S. states are included in the analysis. It is worth noting that we choose not to use disaggregated data to circumvent the high collinearity arising from the construction of agricultural emissions data.

Environmental data come from CAIT-US, a database developed by the World Resources Institute (WRI), which consists of state-level emissions of six major greenhouse gases. The data used in this research is limited to total greenhouse gas (GHG) emissions,

methane (CH_4), and nitrous oxide (N_2O) emissions, all measured in metric tons of CO_2e. The first set of data consists of total GHG emissions including land-use change and forestry (LUCF), which represents net emissions/removals attributable to forest and land use changes. Such data account for the role that deforestation, reforestation, and land use changes play as sources of carbon emissions or as carbon sinks. The remaining data consist of CH_4 and N_2O emissions, respectively. Data for CO_2 emissions are available but are excluded from the analysis due to high correlation with total GHG emissions ($r = 0.92$).

CAIT-US reports emissions across various energy sectors, namely residential, commercial, industrial, transportation, fugitive emissions, industrial processes, agriculture, and waste (WRI, 2015). In addition, it also reports fuel use during cross-border transportation as well as changes in emissions related to LUCF. CAIT-US data are developed based on the State Inventory Tool (SIT) of the Environmental Protection Agency (EPA), which represents an interactive spreadsheet model that helps develop state-level GHG inventories. The SIT default data consists primarily of data collected by federal agencies such as the EPA, the Energy Information Administration (EIA), Federal Highway Administration (FHA), Mineral Management Services (MMS), the USDA, and the U.S. Geological Survey (USGS) as well as other sources such as the Fertilizer Institute (WRI, 2015). While the SIT is also designed to allow for the provision of potentially more reliable data by state agencies, CAIT-US only makes use of SIT's default data to ensure a reasonable degree of consistency across states.

Population data are from the U.S. Census Bureau and represent state midyear estimates. Data for state per capita gross domestic product (GDP) (in chained 2009 dollars), real utilities output (percent of state GDP), real manufacturing output (percent of state GDP), and real oil and natural gas output (percent of state GDP) are from the Bureau of Economic Analysis. In particular, per capita GDP is also known as income and represents a proxy for average state affluence. Data for vehicle miles traveled (VMT) are from the U.S. Department of Transportation's Federal Highway Administration. Finally, data on state organic cropland, organic pasture, and total farmland acreage are from the USDA's Economic Research Service. The total farmland variable is included as a scale variable to control for farming intensity across states.

Using state-level data has important advantages. Such data are from the same sources and ensure a reasonable degree of consistency, accuracy, and reliability. Moreover, U.S. states have a common language and similar social norms and must comply with common federal laws, thus reducing potential unobserved heterogeneity. Of course, unobserved heterogeneity across states arising from demographic, geographic, natural resource, and regulatory idiosyncrasies, amongst others, can raise important concerns, which are undoubtedly legitimate and are addressed in the empirical section.

4.2. Preliminary analysis of the data

Table 2 provides summary statistics of the main variables used in this analysis. Although most variables have 550 longitudinal observations, there are some that suffer from missing observations, thus reducing the sample size to as low as 421 observations. It is also important to note that data for GHG and CH_4 emissions may take negative values for some states, such as Idaho, Montana, Oregon, and Vermont for total GHG and New Hampshire for CH_4. For instance, in New Hampshire the reduction of CH_4 emissions from the conversion of landfill gas to energy may outweigh emissions arising from other sources such as the agricultural sector, which represented barely 0.09% of the state's economy in 2011 (Bureau of Economic Analysis, 2016). Thus, to avoid problems in natural log transformation, a value of 20 metric tons of CO_2e is added to each GHG observation, whereas a value of 5 metric tons of CO_2e is added to each CH_4 observation. The values presented in Table 2 reflect these adjustments.

4.3. Empirical specifications

In order to assess the relationship between organic farming and GHG emissions, we develop a set of models based on the extensive literature on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) approach (e.g. Dietz and Rosa, 1994, 1997; Cramer, 1998; York et al., 2003; Shi, 2003; Cole and Neumayer, 2004; Squalli, 2009, 2010, 2014; Price and Feldmeyer, 2012). Unlike LCA, which is site-specific, the STIRPAT approach relies on observed environmental impact data and appropriate estimators to establish a connection between a set of hypothesized variables. It is based on the IPAT mathematical identity, which posits that $I = P \times A \times T$, where environmental impact (I) is a function of population (P), affluence (A), and technology (T) (Ehrlich and Holdren, 1971). Given that per capita GDP is generally a proxy for affluence, the product of population and affluence is such that $P \times A = GDP$. Thus, the technology component can be written as $T = I/GDP$, which represents impact per unit of GDP. Although the technology component is typically captured by the error term, it can be disaggregated into impact components (York et al., 2003), an approach that we pursue in this paper.

The application of the IPAT identity within a longitudinal regression framework requires for the expression to be rewritten following Dietz and Rosa (1997) as follows:

$$I_{it} = \alpha P_{it}^{\beta} A_{it}^{\gamma} T_{it}^{\delta} \varepsilon_{it} \tag{1}$$

where I in state i during period t is a nonlinear function of P, A, and T and where α, β, γ, and δ are constant terms to be estimated alongside the error term ε. This new expression becomes more meaningful and convenient when log-linearized, resulting in the following specification:

$$\ln I_{it} = \ln \alpha + \beta \ln P_{it} + \gamma \ln A_{it} + \delta \ln T_{it} + \ln \varepsilon_{it} \tag{2}$$

where β, γ, and δ represent ecological elasticities measuring the responsiveness of emissions to changes in corresponding explanatory variables. It is important to note that log transformation yields a number of benefits. First, estimates using log-transformed variables are less sensitive to outliers and heteroskedastic residuals. Second, coefficient estimates can be interpreted as ecological elasticities, measuring the percent responsiveness of the dependent variable to percent changes in an independent variable, net of other factors. Expressing changes in percentage terms rather than in levels simplifies economic interpretations and allays concerns about inconsistent measurement units. Third, the interpretation of coefficient estimates is more meaningful because log transformation scales the data to a common unit of measurement.

The log-linear model above can be applied to address the relationship between organic farming and GHG emissions. The first base model can therefore be specified as follows:

$$\begin{aligned} \ln GHG_{it} = {} & \alpha_0 + \alpha_1 \ln POP_{it} + \alpha_2 \ln GDP_{it} + \alpha_3 (\ln GDP_{it})^2 \\ & + \alpha_4 \ln VMT_{it} + \alpha_5 OIL_{it} + \alpha_6 UTIL_{it} + \alpha_7 MANUF_{it} \\ & + \alpha_8 TRANS_{it} + \alpha_9 \ln FARMLAND_{it} \\ & + \alpha_{10} \ln ORGCROP_{it} + \mu_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where ln total GHG emissions including LUCF for state i in period t

Table 2
Summary statistics.

Variables		Max	Min	SD	Mean	Obs.
ln GHG	Overall	6.7	2.3	0.79	4.63	N = 550
	Between	6.68	2.99	0.79		n = 50
	Within	5.12	2.88	0.14		T = 11
ln CH_4	Overall	4.31	1.4	0.55	2.55	N = 550
	Between	4.21	1.54	0.56		n = 50
	Within	2.81	2.3	0.06		T = 11
ln N_2O	Overall	3.28	−1.82	1.15	1.33	N = 550
	Between	3.11	−1.47	1.15		n = 50
	Within	1.65	0.89	0.1		T = 11
Population	Overall	37,334,410	489,451	6,411,687	5,840,988	N = 550
	Between	35,321,551	515,735	6,459,974		n = 50
	Within	8,570,842	2,991,432	372,289		T = 11
Per capita GDP ($)	Overall	69,787	28,372	8289	44,713	N = 550
	Between	63,913	30,509	7853		n = 50
	Within	56,643	33,125	2859		T = 11
ln VMT	Overall	12.7	8.39	0.98	10.52	N = 550
	Between	12.67	8.49	0.99		n = 50
	Within	10.74	10.21	0.06		T = 11
Oil & natural gas (% of GDP)	Overall	38.05	0	3.91	1.5	N = 511
	Between	19.54	0	3.66		n = 50
	Within	20.01	−3.79	1.11		T = 10.2
Utilities(% of GDP)	Overall	4.37	0.61	0.63	2.12	N = 550
	Between	3.51	0.69	0.57		n = 50
	Within	3.08	1.22	0.28		T = 11
Manufacturing(% of GDP)	Overall	29.81	1.75	5.48	12.46	N = 550
	Between	27.24	1.97	5.34		n = 50
	Within	26.13	4.43	1.42		T = 11
Transportation(% of GDP)	Overall	11.79	1.34	1.51	3.3	N = 550
	Between	9.97	1.43	1.5		n = 50
	Within	5.13	1.79	0.28		T = 11
ln farmland	Overall	18.69	11	1.57	15.95	N = 550
	Between	18.69	11.11	1.59		n = 50
	Within	16.1	15.84	0.03		T = 11
ln organic cropland	Overall	13.12	0.69	2.26	9.01	N = 535
	Between	12.27	4.73	2.18		n = 50
	Within	13.24	3.52	0.77		T = 10.7
ln organic pasture	Overall	14.19	1.61	2.53	7.88	N = 456
	Between	13.03	3.43	2.37		n = 50
	Within	11.93	2.39	1.16		T = 9.12
ln organic cropland × Transportation	Overall	98.81	0.95	14.84	29.84	N = 535
	Between	86.39	6.75	14.56		n = 50
	Within	46.7	−5.3	3.87		T = 10.7

Note: GHG emissions are in metric tons of CO_{2e}. Population data are state midyear estimates. VMT stands for vehicle miles traveled. The farmland, organic cropland, and organic pasture variables are measured in acres.

are estimated with respect to log population (POP), ln real per capita GDP, ln real per capita GDP squared, ln vehicle miles traveled (VMT), output from the utilities sector as percent of state GDP (UTIL), output from the manufacturing sector as percent of state GDP (MANUF), output from the transportation sector as percent of state GDP (TRANS), ln total farmland acreage (FARMLAND), and ln organic cropland acreage (ORGCROP). Augmented specifications are also estimated after adding ln organic pasture acreage (ORGPAST) and an interaction term representing the product between ln ORGCROP and TRANS. The model also includes a state-specific component, μ_i, a year-specific component, μ_t, and an idiosyncratic shock, ε_{it}.

The remaining base models for CH_4 and N_2O emissions are specified as follows:

$$\begin{aligned}\ln CH_{4it} = {} & \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDP_{it} + \beta_3 (\ln GDP_{it})^2 + \beta_4 OIL_{it} \\ & + \beta_5 TRANS_{it} + \beta_6 \ln FARMLAND_{it} \\ & + \beta_7 \ln ORGCROP_{it} + \theta_i + \theta_t + \tau_{it}\end{aligned} \tag{4}$$

$$\begin{aligned}\ln N_2O_{it} = {} & \delta_0 + \delta_1 \ln POP_{it} + \delta_2 \ln GDP_{it} + \delta_3 (\ln GDP_{it})^2 \\ & + \delta_4 \ln VMT_{it} + \delta_5 MANUF_{it} + \delta_6 TRANS_{it} \\ & + \delta_7 \ln FARMLAND_{it} + \delta_8 \ln ORGCROP_{it} + \gamma_i + \gamma_t + \eta_{it}\end{aligned} \tag{5}$$

where Equation (4) includes the primary sources of CH_4 emissions, namely livestock farming, and the production, processing, transportation, storage, distribution, and use of natural gas and petroleum. Equation (5) also controls for the primary sources of N_2O emissions, namely industrial or chemical production, transportation, and farming.

The use of total emissions instead of per capita emissions in all specifications is consistent with Cole and Neumayer (2004) and the variable POP is introduced as a scale variable and to test for the well-known effect of population on emissions. Per capita GDP is also introduced as a quadratic term to control for potential nonlinearity in the relationship between income and greenhouse gas emissions. This is consistent with the Environmental Kuznets Curve hypothesis (Grossman and Krueger, 1995), which posits that emissions increase with income up to a certain level before eventually declining.

The technology variable is decomposed into the OIL, UTIL, MANUF, and TRANS variables, which are used to control for emissions that are driven by large oil and natural gas production, utilities, manufacturing, and transportation sectors, respectively. Any other omitted technology factors will be captured by the error terms ε_{it}, τ_{it}, and η_{it}. Given that CH_4 data omit emissions arising from activities related to oil and natural gas, including the OIL variable serves a confirmatory purpose. Therefore, a properly specified CH_4 model requires the coefficient estimate for OIL to not be statistically significant. We also introduce ln VMT as an explanatory variable to control for the potential effect of the miles driven by vehicles on GHG emissions. Finally, we include an interaction term between ln organic cropland acreage and TRANS in order to assess to what degree the interaction between organic farming and the transportation sector contributes to GHG emissions. This helps estimate how changes in organic cropland acreage affect GHG emissions for given shares of transportation output, thus providing insight on whether the potential environmental benefits of organic food production, if any, are substantial enough to outweigh the environmental harm of transportation output. Transportation is the primary focus in this research because it represents the largest source of emissions and a common factor across conventional and organic food production.

The key variables of interest include ln ORGCROP, ln FARMLAND, ln ORGPAST, and the interaction term between TRANS and ln ORGCROP. The ORGCROP variable represents organic cropland acreage and is used in conjunction with the FARMLAND variable, which represents total farmland acreage. These two variables when jointly included control for emissions arising from the agricultural sector and for the relative size of the organic farming sector. The ORGPAST variable is also included to account for the fact that pasture used for grazing animals do not have the same impact on GHG emissions as organic food production. Special attention must be given to the interaction term. Without it, the coefficient estimate for TRANS would be interpreted as a measure of the partial effect of TRANS on GHG emissions, for given levels of other factors. However, with its inclusion, the effect of TRANS on GHG emissions must be interpreted by taking into account both the coefficient estimate of TRANS and that of the interaction term.

4.4. Estimation method

Unobserved heterogeneity is virtually inevitable and cannot be expected to be independent of the included variables in the empirical specifications. Estimations not accounting for such heterogeneity would suffer from omitted variable bias and would yield biased and inconsistent estimates. Such heterogeneity can arise from time-invariant factors such as demographic distribution, location, natural resource endowment, regulatory regime, and other hard-to-measure factors. The fixed effects estimator allays such concerns due to its ability to control for time-invariant factors, for potential geographic non-independence of data points, and for the potential spillover effects that can arise from being in a particular location.

For completeness and whenever applicable, Equations (3)–(5) and their augmented versions are estimated using one-way (state) random and fixed effects and two-way (state and year) random and fixed effects. The choice of the appropriate estimator is determined using a Hausman test, whereas including the year-specific component is determined using a Wald test. All estimations are completed using standard errors that are cluster-robust to arbitrary heteroskedasticity and arbitrary intragroup correlation. The technical details of the random and fixed effects estimators are extensively covered in econometrics textbooks (e.g. Kennedy, 2008).

5. Results

In order to identify the most suitable estimator, we first make use of a Hausman test for the null hypothesis that the differences in coefficients between random and fixed effects estimations are not systematic. We then test for the inclusion of the year-specific component using a Wald test for the null hypothesis that the coefficient estimates for the year dummies are jointly equal to zero. Table 3 shows that for the GHG model, the null hypothesis is not rejected, favoring random effects. In contrast, however, the null hypothesis for both CH_4 and N_2O models is rejected ($p < 0.01$), providing support for fixed effects.

As for the year-specific component, Table 3 shows that the null hypothesis that the coefficient estimates of all year dummies are jointly statistically significant is rejected for all three models ($p < 0.01$). This suggests that temporal variation must be accounted for by including a set of dummy variables for each year of the data sample except a reference year. Accordingly, dummy variables are introduced for the years 1997 and 2000–2008. The year 2010 is assumed as the reference year and is omitted from the estimations.

5.1. Estimation results for GHG emissions

Tables 4–6 summarize the main estimation results. Column (1) of Table 4 shows random effects estimation results for the base model specified in Equation (3). Column (2) shows estimation results for the augmented specification introducing the interaction term, whereas column (3) shows results for the specification introducing the ln ORGPAST variable. Columns (4) through (6) show results for the same specifications but after accounting for the year-specific component.

The gradual introduction of variables appears to increase the R^2 values of the estimated specifications. However, the specification results in column (3) appear to have relatively similar R^2 values to those in column (2) despite the fact they are based on a smaller sample. The explanatory variables included in the specifications reported in columns (1) and (2) explain about 83% of the variation in GHG emissions with a sample size of 496, whereas those for the specification reported in column (3) explain 82.8% of the variation in GHG emissions with a sample size of 421.

Focusing on column (3) estimation results, the coefficient estimate for population has the expected sign and is statistically significant ($p < 0.01$). The coefficient estimates for oil and natural gas, utilities, and manufacturing also have the expected sign and are statistically significant at the 0.01, 0.05, and 0.01 levels, respectively. As for the variables of interest, the coefficient estimate for ln farmland is positive and statistically significant ($p < 0.01$). This suggests that for a one percent increase in farmland acreage, GHG emissions are expected to increase by 0.13%. On the other hand, the ecological elasticity coefficients for ln organic cropland and ln organic pasture are both negative and statistically significant ($p < 0.05$). This suggests that as organic farming acreage increases by one percent, total GHG emissions are likely to decrease by about

Table 3
Hausman Test for estimator selection and Wald test for the joint significance of year dummies.

	GHG Model	CH_4 Model	N_2O Model
Hausman Test			
χ^2	12.94	49.28	81.48
p value	0.37	0.00	0.00
Wald Test			
χ^2	80.07	7.56	20.43
p value	0.00	0.00	0.00

Table 4
Random Effects estimation results for GHG emissions incl. LUCF ($n = 50$).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ln population	0.400**	0.433**	0.541**	0.434**	0.464**	0.520**
	(0.142)	(0.142)	(0.165)	(0.159)	(0.154)	(0.173)
ln per capita GDP	21.271	23.675	22.139	21.953	24.325*	21.996
	(12.930)	(12.768)	(15.883)	(12.081)	(12.358)	(14.978)
(ln per capita GDP)^2	−0.973	−1.087	−1.012	−0.994	−1.106	−0.999
	(0.600)	(0.593)	(0.737)	(0.560)	(0.573)	(0.696)
ln VMT	0.183	0.148	0.042	0.177	0.146	0.09
	(0.142)	(0.142)	(0.169)	(0.169)	(0.165)	(0.187)
Oil & natural gas share	0.030**	0.030**	0.035**	0.031**	0.032**	0.037**
	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)
Utilities share	0.097**	0.093**	0.068*	0.048	0.04	0.004
	(0.029)	(0.030)	(0.034)	(0.052)	(0.055)	(0.064)
Manufacturing share	0.017**	0.017*	0.020**	0.017*	0.017*	0.020*
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
Transportation share	0.019	−0.044	−0.058	0.031	−0.032	−0.042
	(0.027)	(0.032)	(0.055)	(0.027)	(0.027)	(0.051)
ln farmland	0.118**	0.118**	0.131**	0.103**	0.103**	0.105**
	(0.036)	(0.035)	(0.036)	(0.034)	(0.033)	(0.034)
ln organic cropland	−0.015*	−0.039*	−0.059*	−0.001	−0.025	−0.04
	(0.006)	(0.018)	(0.027)	(0.006)	(0.015)	(0.027)
ln organic cropland × Transportation		0.007	0.01		0.008	0.01
		(0.005)	(0.007)		(0.004)	(0.007)
ln organic pasture			−0.007*			−0.002
			(0.003)			(0.004)
Constant	−121.717	−134.381	−127.066	−126.976	−139.457*	−126.921
	(69.960)	(69.063)	(85.718)	(65.535)	(66.970)	(80.822)
Year dummies	No	No	No	Yes	Yes	Yes
N	496	496	421	496	496	421
Overall R^2	0.83	0.831	0.828	0.819	0.82	0.81

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported with their corresponding robust standard errors in parentheses. The results reported in columns (1) and (4) are for Equation (3). The results in the remaining columns are for augmented versions. Parameters for the random-error component range between −0.788 and 0.96 with a mean value ≈0. Parameters for the year-specific component range between 0.014 and 0.141 with a mean value of 0.076 (2010 reference year). Parameters for the idiosyncratic shock (averaged over time) range between −0.018 and 0.014 with a mean value of −0.0004.

Table 5
Fixed Effects estimation results for CH_4 emissions ($n = 50$).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ln population	0.517**	0.525**	0.782**	0.683**	0.664**	0.870**
	(0.164)	(0.161)	(0.181)	(0.173)	(0.168)	(0.226)
ln per capita GDP	−0.298	1.576	1.748	3.138	5.059	4.584
	(7.374)	(6.474)	(4.847)	(6.634)	(6.061)	(4.524)
(ln per capita GDP)^2	0.018	−0.07	−0.072	−0.13	−0.22	−0.194
	(0.347)	(0.305)	(0.229)	(0.312)	(0.284)	(0.212)
Oil & natural gas share	0.015	0.014	0.011	0.011	0.009	0.009
	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Transportation share	0.039*	−0.027	−0.064	0.036	−0.036	−0.04
	(0.016)	(0.025)	(0.038)	(0.022)	(0.027)	(0.043)
ln farmland	0.059	0.116	0.156	−0.058	0.008	0.07
	(0.233)	(0.226)	(0.203)	(0.240)	(0.234)	(0.233)
ln organic cropland	−0.01	−0.033*	−0.052**	−0.008	−0.033*	−0.047**
	(0.006)	(0.013)	(0.010)	(0.006)	(0.014)	(0.011)
ln organic cropland × Transportation		0.007*	0.012**		0.008**	0.010**
		(0.003)	(0.003)		(0.003)	(0.003)
ln organic pasture			−0.007			−0.007
			(0.004)			(0.004)
Constant	−5.085	−15.884	−21.789	−25.583	−36.304	−38.191
	(38.298)	(33.017)	(25.276)	(33.854)	(30.596)	(23.305)
Year dummies	No	No	No	Yes	Yes	Yes
N	496	496	421	496	496	421
Overall R^2	0.4	0.478	0.436	0.183	0.266	0.327

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported with their corresponding robust standard errors in parentheses. The results reported in columns (1) and (4) are for Equation (4). The results in the remaining columns are for augmented versions. Parameters for the fixed-error component range between −1.252 and 1.654 with a mean value of −0.028. Parameters for the year-specific component range between −0.023 and 0.073 with a mean value of 0.025 (2010 reference year). Parameters for the idiosyncratic shock (averaged over time) ranges between −0.028 and close to zero with a mean value of −0.0005.

0.06% and as organic pasture acreage increases by one percent, GHG emissions are expected to decrease by about 0.007%. Finally, neither the coefficient estimate for the transportation variable nor that for the interaction term are statistically significant, suggesting that the effect of transportation output on GHG emissions does not vary with changes in organic farming.

The introduction of the year-specific component yields a number of important changes. All specifications in columns (4) through

Table 6
Fixed Effects estimation results for N_2O emissions ($n = 50$).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ln population	−1.013**	−0.956**	−0.962**	0.062	0.024	0.006
	(0.210)	(0.220)	(0.209)	(0.278)	(0.269)	(0.342)
ln per capita GDP	26.529*	31.129**	37.225**	32.861**	36.479**	41.012**
	(11.199)	(8.793)	(10.847)	(7.917)	(6.874)	(7.854)
(ln per capita GDP)^2	−1.242*	−1.457**	−1.744**	−1.501**	−1.673**	−1.887**
	(0.525)	(0.412)	(0.509)	(0.368)	(0.317)	(0.364)
ln VMT	0.028	−0.027	0.063	−0.048	−0.078	0.082
	(0.237)	(0.240)	(0.222)	(0.242)	(0.242)	(0.213)
Manufacturing share	0.008	0.009	0.012*	−0.001	0.001	0.002
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Transportation share	0.035	−0.140**	−0.304**	0.047	−0.101**	−0.200*
	(0.024)	(0.043)	(0.077)	(0.035)	(0.035)	(0.085)
ln farmland	−0.363	−0.215	−0.34	−0.455	−0.325	−0.364
	(0.489)	(0.463)	(0.548)	(0.381)	(0.372)	(0.444)
ln organic cropland	−0.027**	−0.088**	−0.160**	−0.011	−0.063**	−0.110**
	(0.008)	(0.025)	(0.027)	(0.008)	(0.019)	(0.024)
ln organic cropland × Transportation		0.020**	0.035**		0.016**	0.026**
		(0.005)	(0.007)		(0.004)	(0.006)
ln organic pasture			0.004			0.008
			(0.004)			(0.004)
Constant	−119.413	−146.09**	−176.61**	−171.71**	−191.51**	−215.820**
	(59.828)	(46.904)	(55.944)	(42.928)	(37.682)	(42.445)
Income turning point ($)	43,396	43,432	43,199	56,742	54,463	52,510
Year dummies	No	No	No	Yes	Yes	Yes
N	535	535	454	535	535	454
R^2	0.65	0.518	0.612	0.599	0.614	0.47

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported with their corresponding robust standard errors in parentheses. The results reported in columns (1) and (4) are for Equation (5). The results in the remaining columns are for augmented versions. Parameters for the fixed-error component range between −4.783 and 2.409 with a mean value of −0.116. Parameters for the year-specific component range between 0.018 and 0.322 with a mean value of 0.164 (2010 reference year). Parameters for the idiosyncratic shock (averaged over time) are infinitesimal and thus reported as equal to zero.

(6) yield similar results. The coefficient estimates for population, oil and natural gas, manufacturing, and farmland maintain the same sign and remain statistically significant. However, the coefficient estimate for utilities, ln organic cropland, and ln organic pasture are no longer statistically significant. This suggests that organic farming has no statistically significant impact on GHG emissions. However, given that GHG emissions consist of CO_2, CH_4, and N_2O, it is difficult to assign any interpretation to these results without examining the estimation results for CH_4 and N_2O emissions, which are known to have a strong connection with agricultural activities.

5.2. Estimation results for CH_4 emissions

Table 5 summarizes the fixed effects estimation results for CH_4 emissions. Column (1) reports estimation results for the specification described by Equation (2), whereas columns (2) and (3) augment this specification with the interaction term and ln ORGPAST, respectively. Columns (4) through (6) report the same specifications but after introducing the year-specific component. It is worth noting that the reported intercept parameters represent estimates for average state-specific fixed effects. These are the time-invariant state-specific factors contributing to GHG emissions other than those already included in Equation (4).

As expected, the coefficient estimate for population is positive and statistically significant ($p < 0.01$) across all specifications. As described earlier, the OIL variable could have been excluded from the model due to the fact that the data used omit CH_4 emissions from oil and natural gas. This is confirmed by the fact that the coefficient estimate for OIL is not statistically significant across all estimations. The coefficient estimate for transportation output is statistically significant ($p < 0.05$) but only in the base specification in column (1). Adding the interaction term in column (2) not only increases the R^2 value of the specification but also results in a negative and statistically significant coefficient estimate for ln organic cropland and a positive and statistically significant coefficient estimate for the interaction term.

The augmented specification in column (3) yields similar results in addition to a slight increase in the size of the relevant coefficient estimates. Furthermore, the introduction of the year-specific component leaves the estimation results relatively unchanged. Focusing on the results in column (6), the coefficient estimate for the interaction term is positive and statistically significant, suggesting that the effect of organic farming acreage on CH_4 emissions varies with transportation output. This means that as transportation output takes different values, the effect of organic farming acreage on GHG emissions changes accordingly. The effect of organic farming acreage on CH_4 emissions for given shares of transportation output can be expressed by factoring out ln organic cropland in Equation (2) to derive the marginal effect, which can be written as:

$$\beta_{me} = -0.047 + 0.010\ TRANS \tag{6}$$

Setting $\beta_{me} = 0$ and solving for TRANS, we find an approximate value of 4.46, which suggests that an increase in organic cropland acreage will mitigate CH_4 emissions when TRANS < 4.46% and will increase CH_4 emissions when TRANS > 4.46%. It is worth noting that although the coefficient estimate for ln organic cropland acreage is negative and statistically significant ($p < 0.01$), it does not mean that organic farming mitigates CH_4 emissions, net of other sources of emissions. Rather, since ln organic cropland interacts with transportation output, it must be interpreted for given shares of transportation output. In other words, a one percent increase in organic crop acreage would result in a 0.047% decrease in CH_4 emissions when transportation output takes a value of zero. This is evidently unrealistic and does not capture the true interaction between organic farming and transportation output.

Based on Table 2, transportation output shares range between 1.34 and 11.78. A predictive margins plot can provide insight on

how organic farming affects CH_4 emissions for given shares of transportation output. Fig. 2 shows a predictive margins plot where the lines starting from the left wing represent shares for transportation output ranging from 1 to 11. Once again, for low shares of transportation output, an increase in organic farming appears to mitigate CH_4 emissions. Once transportation output exceeds the 4.46% threshold, the effect of organic farming on emissions reverses to start causing CH_4 emissions to rise.

5.3. Estimation results for N_2O emissions

Table 6 summarizes the estimation results for N_2O emissions. Just like previous estimations, column (1) shows the estimation results of the base specification as described by Equation (3). This is followed by the estimation results of two specifications that are augmented with the interaction term and ln organic pasture, respectively. Columns (4) through (6) show estimation results for the same specifications but with the introduction of the year-specific component.

The estimation results reported in column (1) show that the coefficient estimate for population is negative and statistically significant ($p < 0.01$). This is somewhat surprising as a rising population is expected to boost agricultural output, subsequently increasing N_2O emissions (IPCC, 2015). This negative sign could reflect the interaction between population, total farmland acreage, and organic acreage or the missing year-specific component. In fact, with the introduction of year dummies, the coefficient estimate for ln population is no longer negative and the overall results remain relatively unaffected.

With the exception of the coefficient estimates for population, which become positive and lose statistical significance, all other results remain relatively unchanged after introducing the year-specific component. Based on the estimation results in column (6), there is evidence of an EKC, suggesting that N_2O emissions increase with income up to a turning point of $52,510 after which emissions decline. The coefficient estimates for transportation output, ln organic cropland, and the interaction term are also all statistically significant ($p < 0.05$, $p < 0.01$, and $p < 0.01$, respectively).

Interpreting the effect of transportation output on N_2O emissions requires an analysis similar to the one completed for CH_4 emissions. Since the coefficient estimates for ln organic cropland and for the interaction term are statistically significant, the main effect of organic farming acreage on N_2O emissions will vary with values of transportation output. This can be expressed with the following expression and also visualized using predictive margins plots.

$$\delta_{me} = -0.11 + 0.026\ TRANS \tag{7}$$

Setting $\delta_{me} = 0$ and solving for TRANS yields an approximate value of 4.16, which suggests that an increase in organic farming will mitigate N_2O emissions when TRANS < 4.16% and will increase N_2O emissions when TRANS > 4.16%. Fig. 3 shows a predictive margins plot of the effect of organic farming on N_2O emissions, which confirms these findings.

5.4. Sensitivity analysis

In order to test the reliability of our estimates, we assess whether they might have been biased by potentially influential observations. We derive median and median average deviation (MAD) values for each state. This approach is superior to using the standard deviation around the mean, which is known to be sensitive to outliers (Leys et al., 2013). To be consistent with previous research (e.g. Leys et al., 2013), we use the following moderately conservative decision criterion:

$$\frac{x_i - \text{Median}}{MAD} > |\pm 2.5| \tag{8}$$

which suggests that observations for which the deviation from the median exceeds 2.5 times the median average deviation should be considered for potential exclusion.

There are at least six states that meet the decision criterion and that could be considered outliers. These states are Vermont, Maine, New York, California, Idaho, and Wisconsin. After excluding them from our sample, we re-estimate our models using the same estimators described in Section 4.4. Table 7 summarizes estimation results based on the augmented specifications reported in Column (6) of the previous tables. A noteworthy change is in the GHG estimation, which shows increased statistical significance for a number of variables. There is now evidence of an EKC with an estimated turning point of $53,673 in addition to evidence that increased organic farming acreage would lower GHG emissions. More specifically, the parameter for ln ORGCROP is negative and statistically significant ($p < 0.05$), suggesting that a one percent

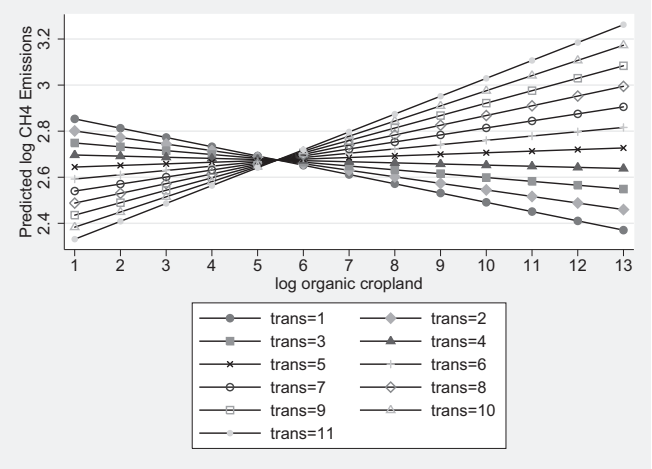

Fig. 2. Predictive margins plot of the effect of organic farming on CH_4 emissions for given shares of transportation output.

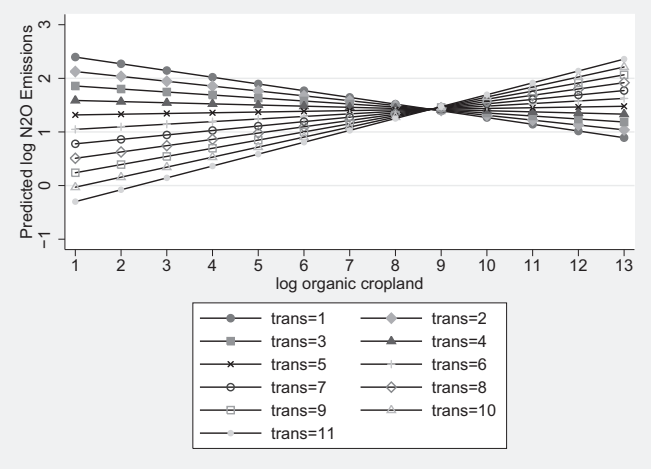

Fig. 3. Predictive margins plot of the effect of organic farming on N_2O emissions for given shares of transportation output.

Table 7
Estimation results without outliers ($n = 44$).

Variables	GHG	CH_4	N_2O
ln population	0.637***	0.815***	0.078
	(0.238)	(0.247)	(0.422)
ln per capita GDP	29.36*	6.575	46.172***
	(16.42)	(5.469)	(8.791)
(ln per capita GDP)^2	−1.348*	−0.288	−2.122***
	(0.764)	(0.257)	(0.409)
ln VMT	−0.0436		−0.264
	(0.245)		(0.275)
Oil & natural gas share	0.0382***	0.009	
	(0.0122)	(0.008)	
Utilities share	−0.00710		
	(0.0581)		
Manufacturing share	0.0216***		0.000
	(0.00763)		(0.005)
Transportation share	−0.0604	−0.046	−0.181**
	(0.0500)	(0.044)	(0.082)
ln farmland	0.102***	0.122	−0.500
	(0.0361)	(0.236)	(0.466)
ln organic cropland	−0.0489*	−0.050***	−0.102***
	(0.0282)	(0.011)	(0.022)
ln organic cropland × Transportation	0.0121	0.011***	0.025***
	(0.00768)	(0.003)	(0.006)
ln organic pasture	2.84e-05	−0.008**	0.008*
	(0.00407)	(0.004)	(0.005)
Constant	−166.0*	−48.696*	−239.398***
	(88.65)	(28.937)	(50.823)
Income turning point ($)	53,673		53,146
Year dummies	Yes	Yes	Yes
N	360	360	390
R^2	0.754	0.413	0.553

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Coefficient estimates are reported with their corresponding robust standard errors in parentheses. The random-effects estimator is used for the GHG model, whereas the fixed-effects estimator is used for the CH_4 and N_2O models.

increase in organic farming acreage could reduce GHG emissions by 0.049%. Finally, the relevant parameters in the CH_4 and N_2O estimations have changed negligibly with the exclusion of outliers, leaving our previous results and conclusions unchanged.

6. Discussion and conclusions

About ten years ago, The Economist (2006) warned that organic farming was so unsustainable that its global adoption could result in the virtual destruction of the rain forest. The true short and long-term environmental benefits of organic farming are not known and likely in flux as organic practices become widespread and mature. Our poor understanding of the environmental impact of organic farming is largely due to the fact that most relevant research often lacks generalizability and fails to exhibit consistency in the assessment of food production's environmental impact. Such research has varied across products, product groups, geography, methodology, and data, thus resulting in mixed messages and confusion. Although organic farming may lag behind conventional farming in terms of land use and yield, it undeniably provides important ecosystem services. Organic farming practices are by design sustainable in the role they play in maintaining optimal soil health, increasing carbon sequestration, and reducing GHG emissions. Yet, various articles in the media and research outlets (e.g. Gray, 2015; McGee, 2015; Paarlberg, 2013) make an effort to discredit organic food production on the grounds that it cannot be scaled without causing environmental harm. Such parties usually focus their attention on conventional farming practices for their ability to take advantage of technological improvements that are designed to increase yield, but fail to acknowledge the resulting potentially irreparable environmental harm. Most importantly, they often base their contentions on speculation, questionable, inadequate, or non-existent empirical evidence.

This paper provides such empirical evidence. After accounting for other sources of emissions and potentially influential observations, we find that one percent increase in organic farming acreage could decrease GHG emissions by 0.049%. We also find that the impact of organic farming on CH_4 and N_2O emissions varies with the transportation output share. More specifically, growth in organic farming is expected to decrease CH_4 emissions for transportation output shares below 4.46% and to increase CH_4 emissions for shares above 4.46%. In addition, growth in organic farming is expected to mitigate N_2O emissions for transportation output shares below 4.16% and to increase N_2O emissions for shares beyond 4.16%. These thresholds are evidently more meaningful when put in context. Based on the data used in this paper, only seven states currently have average transportation output shares that exceed the 4.46% threshold. These states include Alaska (9.76%), Nebraska (7.67%), Wyoming (5.93%), Tennessee (4.84%), Arkansas (4.75%), Montana (4.73%), and Kentucky (4.56%). Furthermore, only eight states, including the seven listed above and North Dakota (4.43%), currently have transportation output shares that exceed the 4.16% threshold.

It is worth noting that states with a large organic farming sector do not necessarily have high transportation output. The variables ln organic cropland and transportation output are virtually uncorrelated ($r = 0.08$) and transportation output is weakly and negatively correlated with organic cropland share (% of total farmland) ($r = -0.24$). Organic farming is evidently not the only contributing factor to emissions. California and Vermont are important examples illustrating this issue. California on average has the most organic acreage in the country but its transportation output share ranks 37th at 2.44%. In contrast, Vermont has the largest share of organic cropland (% of total farmland) but takes the 43rd spot in transportation output with 2.09%. Thus, at the current transportation output shares, growth in organic farming is expected to mitigate CH_4 and N_2O emissions across most states.

The findings related to the interaction between transportation output and organic cropland may have a key plausible explanation. The NOP's standards that restrict the use of synthetic inputs in particular reduce the shelf life of organic food and force most of its distribution into local markets. This suggests that energy use in transporting organic food is likely lower than that for conventionally grown food, consistent with previous research (e.g. Mäder et al., 2002; IFOAM, 2009; Rodale Institute, 2014). Furthermore, given the fact that less than one percent of farming acreage is devoted to organic farming, the environmental benefits of organic farming practices are likely imperceptible when the transportation sector contributes a relatively large share to state GDP. Thus, transportation output must fall below the identified threshold for the environmental harm of transportation output embodied in organic food production to be too negligible to outweigh the environmental benefits of organic farming practices.

Current organic farming practices can already allay many of the environmental concerns about conventional agricultural and play an important role in mitigating GHG emissions. However, scaling organic farming to meet increasing demand for organically grown food calls for an enhancement of farming practices and the movement towards increased sustainability. Regenerative organic agriculture and its management practices are potentially significant means to sequester more than current global annual emissions and to reverse the greenhouse effect (Rodale Institute, 2014). Regenerative organic agriculture's premise lies on nature's ability to regenerate and correct imbalances internally rather than through external inputs. This requires the creation of an ecosystem

endowed with diverse and symbiotic populations of plants, insects, and organic matter. Indeed, the shifting of current cropland and pasture to regenerative organic agriculture is expected to sequester up to 111% of annual carbon emissions, thus resulting in annual negative emissions (Rodale Institute, 2014).

An important channel through which regenerative organic farming can mitigate GHG emissions is by minimizing soil erosion and runoff through the use of conservation tillage (CT). CT involves leaving at least 30% of the previous year's crop residue on fields to minimize soil erosion, runoff, and to maintain organic material into the soil (Abdalla et al., 2013). CT is expected to improve soil health and the soil's ability to sequester more carbon. Thus, replacing conventional tillage practices with CT is expected to reduce GHG emissions through the soil's ability to sequester more carbon.

This paper faces some methodological limitations. Contrary to LCA studies, which yield inferences on the various stages of organic food production's lifecycle, the present analysis makes general state-level inferences. In addition, there is concern that omitted variable bias may result in not rejecting the null hypothesis because of potentially large residual error and the error in estimating other variables. In fact, this is an issue that virtually affects all studies applying multiple regression analysis. This paper allays some of these concerns by using random effects and fixed effects estimators and a nonlinear STIRPAT-inspired empirical model that is consistent with a large and established literature. These factors jointly limit the bias arising from omitting variables potentially highly correlated with GHG emissions.

There are also data limitations. First, although the environmental data we use account for sequestered carbon arising from land use and forestry management, they do not capture stored soil carbon particularly attributed to organic farming practices. Thus, the potential environmental benefits of organic food production may be even larger than those presented in this research. Second, the accuracy of the data is called into question due to the use of SIT default data, which ignores potentially more reliable activity data supplied by individual states. Our inability to identify deficiencies is constrained by the absence of such activity data in a consistent way within the public domain to permit detailed state-by-state audits. Third, simplifying assumptions in the EPA's methodology introduces further uncertainties. For instance, the SIT assumes that landfills across all locations have the same type of waste, which is inconsistent with reality. Fourth, estimates produced by CAIT-US suffer from data omissions. In particular, CAIT-US excludes CH_4 emissions arising from activities related to oil and natural gas, emissions from the production of nitric acid, adipic acid, HFCF-22, and various minerals, and emissions from industrial wastewater (WRI, 2015).

There are a number of potential improvements to our specifications. The estimated CH_4 models could have benefited from the inclusion of variables accounting for municipal solid waste from homes and businesses as well as the conversion of CH_4 emissions to energy, cross-state diversion, disposal, and transfer of municipal solid waste. The N_2O models could also benefit from the inclusion of a variable capturing agricultural soil management (i.e. the use of nitrogen-based fertilizers). However, to the authors' knowledge, no appropriate data are available at the state level. Finally, transportation data do not account for movements across state borders, which could be significant for export-driven states. Although we do not identify a remedy, we expect the use of fixed effects to control for the distribution of exports across states, which does not likely vary significantly over time.

The current study provides evidence supporting potential GHG mitigation benefits associated with organic food production. It is our contention that transiting our food production system to organic farming can be environmentally, ecologically, and economically sustainable. Of course, organic farming practices must be viewed as moving targets that can always benefit from further improvements. In particular, the strict adhesion to a fixed set of principles by organic farming could be seen as a barrier to progress rather than an advantage. A farming activity that is not flexible enough to take advantage of scientific discoveries cannot be sustainable. For instance, modern conventional farming has limited its environmental impact by making use of pest-resistant genetically modified seeds and precision farming (e.g. application of fertilizers to specific areas) using GPS-based technologies (Paarlberg, 2013). In addition, integrated farming, which involves combining best organic and conventional practices, has become a promising system with its ability to reduce energy use and global warming potential (Tuomisto et al., 2012a).

We see several possible contributions of this work. This analysis adds weight to the message echoed in previous LCA research that organic farming yields environmental benefits. It also contributes a new and robust methodological dimension to a large data-driven framework and discourse on the environmental effect of farming practices. We believe that more effort should be directed towards the development of accurate inventories that reflect important environmental metrics. Policymakers and scientists can build on these results to further develop the evidence base and policies needed to quantify and maximize the benefits of adopting organic practices. Our analysis does not include all potential pathways through which GHG benefits could be realized. Applied agricultural research could specifically elucidate the relationship between on-farm practices and changes in energy inputs and other key metrics, such as soil carbon and microbial activity, for different crops, conditions, and climates. Such effort is needed and would augment the insight gained from our study.

References

Abdalla, M., Osborne, B., Lanigan, G., Forristal, D., Williams, M., Smith, P., Jones, M., 2013. Conservation tillage systems: a review of its consequences for greenhouse gas emissions. Soil Use Manag. 29, 199–209.

Ayres, R.U., 1995. Life cycle analysis: a critique. Resour. Conserv. Recycl. 14, 199–223.

Bellarby, J., Foereid, B., Hastings, A., 2008. Cool Farming: Climate Impacts of Agriculture and Mitigation Potential. Greenpeace International, Amsterdam (NL).

Bhat, M.G., English, B.C., Turhollow, A.F., Nyangito, H.O., 1994. Energy in Synthetic Fertilizers and Pesticides: Revisited. Oak Ridge National Laboratory, Knoxville, TN.

Bos, J.F.F.P., De Haan, J., Sukkel, W., 2007. Energieverbruik, broeikasgasemissies en koolstofopslag: de biologische en gangbare landbouw vergeleken (Energy consumption, greenhouse gas emissions and carbon sequestration: comparing organic and conventional agriculture). Plant Research International Wageningen.

Bureau of Economic Analysis, 2016. GDP and Personal Income Regional Data.

Cole, M.A., Neumayer, E., 2004. Examining the impact of demographic factors on air pollution. Popul. Environ. 26, 5–21.

Cooper, J., Butler, G., Leifert, C., 2011. Life cycle analysis of greenhouse gas emissions from organic and conventional food production systems, with and without bio-energy options. NJAS - Wageningen J. Life Sci. 58, 185–192.

Cramer, J.C., 1998. Population growth and air quality in California. Demography 35, 45–56.

Dakhlalla, A.O., Parajuli, P.B., Ouyang, Y., Schmitz, D.W., 2016. Evaluating the impacts of crop rotations on groundwater storage and recharge in an agricultural watershed. Agric. Water Manag. 163, 332–343.

Dietz, T., Rosa, E.A., 1994. Rethinking the environmental impacts of population, affluence and technology. Hum. Ecol. Rev. 1, 277–300.

Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO2 emissions. Proc. Natl. Acad. Sci. U. S. A. 94, 175–179.

Dyckhoff, H., Kasah, T., 2014. Time horizon and dominance in dynamic life cycle assessment. J. Ind. Ecol. 18, 799–808.

Ehrlich, P.R., Holdren, J.P., 1971. Impact of population growth. Science 171, 1212–1217.

Fließbach, A., Oberholzer, H.-R., Gunst, L., Mäder, P., 2007. Soil organic matter and biological soil quality indicators after 21 years of organic and conventional farming. Agric. Ecosyst. Environ. 118, 273–284.

Ghimire, R., Norton, U., Bista, P., Obour, A.K., Norton, J.B., 2017. Soil organic matter, greenhouse gases and net global warming potential of irrigated conventional, reduced-tillage and organic cropping systems. Nutrient Cycl. Agroecosyst. 107, 49–62.

Gray, R., 2015. Is organic Farming Making Climate Change Worse? Demand for 'Sustainable' Food has Increased Greenhouse Gas Emissions. Daily Mail. July 17.
Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110, 353–377.
Hartwig, N.L., Ammon, H.U., 2002. Cover crops and living mulches. Weed Sci. 50, 688–699.
IFOAM, 2009. The Contribution of Organic Agriculture to Climate Change Mitigation. International Federation of Organic Agriculture Movements. http://goo.gl/y6MI7x.
IPCC, 2015. Climate Change 2014: Mitigation of Climate Change Volume 3. Cambridge University Press.
Jordan, R., Müller, A., Oudes, A., 2009. High Sequestration, Low Emission, Food Secure Farming. Organic Agriculture-a Guide to Climate Change & Food Security. IFOAM and IFOAM EU Group.
Kennedy, P., 2008. A Guide to Econometrics. Wiley-Blackwell.
Kuepper, G., 2010. A Brief Overview of the History and Philosophy of Organic Agriculture. Kerr Center for Sustainable Agriculture, Poteau, OK.
Lee, K.S., Choe, Y.C., Park, S.H., 2015. Measuring the environmental effects of organic farming: a meta-analysis of structural variables in empirical research. J. Environ. Manag. 162, 263–274.
Leifeld, J., Reiser, R., Oberholzer, H.-R., 2009. Consequences of conventional versus organic farming on soil carbon: results from a 27-year field experiment. Agron. J. 101, 1204–1218.
Leys, C., Ley, C., Klein, O., Bernard, P., Licata, L., 2013. Detecting outliers: do not use standard deviation around the mean, use absolute deviation around the median. J. Exp. Soc. Psychol. 49, 764–766.
Lori, M., Symnaczik, S., Mäder, P., De Deyn, G., Gattinger, A., 2017. Organic farming enhances soil microbial abundance and activitya meta-analysis and meta-regression. PLoS One 12, e0180442.
Luske, B., van der Kamp, J., 2009. Carbon Sequestration Potential of Reclaimed Desert Soils in Egypt. Louis Bolk Instituut & Soil and More International.
Mäder, P., Fliessbach, A., Dubois, D., Gunst, L., Fried, P., Niggli, U., 2002. Soil fertility and biodiversity in organic farming. Science 296, 1694–1697.
McGee, J.A., 2015. Does certified organic farming reduce greenhouse gas emissions from agricultural production? Agric. Hum. Val. 32, 255–263.
Niggli, U., Fließbach, A., Hepperly, P., Scialabba, N., 2009. Low greenhouse gas agriculture: mitigation and adaptation potential of sustainable farming systems. Ökologie & Landbau 141, 32–33.
Northbourne, L., 2003. Look to the Land. Sophia Perennis.
OTA, 2016. Fact Sheet: State of the Organic Industry. http://goo.gl/OtLkJn.
Paarlberg, R., 2013. Food Politics: what Everyone Needs to Know. Oxford University Press.
Paull, J., 2014. Lord Northbourne, the man who invented organic farming, a biography. J. Org. Syst. 9, 31–53.
Petersen, S.O., Regina, K., Pöllinger, A., Rigler, E., Valli, L., Yamulki, S., Esala, M., Fabbri, C., Syväsalo, E., Vinther, F.P., 2006. Nitrous oxide emissions from organic and conventional crop rotations in five European countries. Agric. Ecosyst. Environ. 112, 200–206.
Pimentel, D., Hepperly, P., Hanson, J., Douds, D., Seidel, R., 2005. Environmental, energetic, and economic comparisons of organic and conventional farming systems. Bioscience 55, 573–582.
Price, C.E., Feldmeyer, B., 2012. The environmental impact of immigration: an analysis of the effects of immigrant concentration on air pollution levels. Popul. Res. Pol. Rev. 31, 119–140.
Reganold, J.P., Glover, J.D., Andrews, P.K., Hinman, H.R., 2001. Sustainability of three apple production systems. Nature 410, 926–930.
Rodale Institute, 2014. Regenerative Organic Agriculture and Climate Change. http://goo.gl/BtjUUP.
Sandhu, H.S., Wratten, S.D., Cullen, R., Case, B., 2008. The future of farming: the value of ecosystem services in conventional and organic arable land. an experimental approach. Ecol. Econ. 64, 835–848.
Shi, A., 2003. The impact of population pressure on global carbon dioxide emissions, 1975–1996: evidence from pooled cross-country data. Ecol. Econ. 44, 29–42.
Squalli, J., 2009. Immigration and environmental emissions: a US county-level analysis. Popul. Environ. 30, 247–260.
Squalli, J., 2010. An empirical assessment of US state-level immigration and environmental emissions. Ecol. Econ. 69, 1170–1175.
Squalli, J., 2014. Is obesity associated with global warming? Publ. Health 128, 1087–1093.
Steiner, R., 2004. Agriculture Course: the Birth of the Biodynamic Method: Eight Lectures Given in Koberwitz, Silesia, between 7 and 16 June 1924. Rudolf Steiner Press.
Syväsalo, E., Regina, K., Turtola, E., Lemola, R., Esala, M., 2006. Fluxes of nitrous oxide and methane, and nitrogen leaching from organically and conventionally cultivated sandy soil in Western Finland. Agric. Ecosyst. Environ. 113, 342–348.
The Economist, 2006. Good Food? http://www.economist.com/node/8381375.
Tuomisto, H.L., Hodge, I., Riordan, P., Macdonald, D.W., 2012a. Comparing global warming potential, energy use and land use of organic, conventional and integrated winter wheat production. Ann. Appl. Biol. 161, 116–126.
Tuomisto, H.L., Hodge, I., Riordan, P., Macdonald, D.W., 2012b. Does organic farming reduce environmental impacts?–A meta-analysis of European research. J. Environ. Manag. 112, 309–320.
USDA, 2013. Organic Production. United States Department of Agriculture, Economic Research Service.
Vázquez-Rowe, I., Rege, S., Marvuglia, A., Thénie, J., Haurie, A., Benetto, E., 2013. Application of three independent consequential LCA approaches to the agricultural sector in Luxembourg. Int. J. Life Cycle Assess. 18, 1593–1604.
Venter, Z.S., Jacobs, K., Hawkins, H.-J., 2016. The impact of crop rotation on soil microbial diversity: a meta-analysis. Pedobiologia 59, 215–223.
Wood, R., Lenzen, M., Dey, C., Lundie, S., 2006. A comparative study of some environmental impacts of conventional and organic farming in Australia. Agric. Syst. 89, 324–348.
WRI, 2015. CAIT Climate Data Explorer-us State GHG Emissions Documentation. World Resources Institute.
York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol. Econ. 46, 351–365.